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# Hierarchical Delta-Attention Method for Multimodal Fusion

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## Abstract

In vision and linguistics; the main input modalities are facial expressions, speech patterns, and the words uttered. The issue with analysis of any one mode of expression (Visual, Verbal or Vocal) is that lot of contextual information can get lost [3, 16]. This asks researchers to inspect multiple modalities to get a thorough understanding of the cross-modal dependencies and temporal context of the situation to analyze the expression [20]. This work attempts at preserving the *long-range dependencies* [22] within and across different modalities, which would be bottlenecked by the use of recurrent networks and adds the concept of *delta-attention* [28] to focus on local differences per modality to capture the idiosyncrasy of different people. We explore a cross-attention fusion technique to get the global view of the emotion expressed through these delta-self-attended modalities, in order to fuse all the local nuances and global context together. The addition of attention is new to the multimodal fusion field and currently being scrutinized for on what stage the attention mechanism should be used, this work achieves competitive accuracy for overall and per-class classification which is close to the current state-of-the-art [22] with almost half number of parameters.

## 1 Introduction

In computer vision and natural language processing; the tasks like emotion recognition, sentiment analysis, personality trait recognition, audio source localization, audio diarization are very important for the use cases of product and advertisement market value analysis, and personal assistant to the people with visible or invisible disabilities. The task of emotion recognition has attracted attention of the machine learning community [9, 7]. Emotions can be detected from facial expressions, from speech patterns, and from words uttered. The issue with analysis of any one mode of expression (Visual, Verbal or Vocal) is that lot of contextual information can get lost [3, 16]. E.g., a sarcastic remark like “That sounds great” can be uttered with a smirk, in an angry or indignant voice. If we only analyze the verbal modality, we would miss the context of the situation (imparted by visuals and vocals). This asks researchers to inspect multiple modalities to get a thorough understanding of the cross-modal dependencies and temporal context of the situation to analyze the emotion [20].

The current problems regarding human multimodal behaviors during social interactions can have consequences on mental health and invisible disabilities. Along with the observation of health impacts of social anxiety, the multimodal fusion techniques can also explore the task of image captioning which deals with looking at a video or an image and describing the context of the content verbally. These kinds of systems help the visually impaired people and can be a great addition to the personal assistants available in the market like Alexa, Siri, Cortana, Google Assistant and such.

This work plans to explore 3 main issues with current techniques addressing multimodal fusion for the visuals, verbals, and vocals:

1. There is an important distinction between emotion and mood, the main difference being the timescale of both concepts. While emotion itself is short-term, its effects on a person’s mood might persist for a relatively long time. There are recurrent networks [22] to cover long-range dependencies over and across the modalities but they suffer from exploding or vanishing gradient problems and long-sequence bottleneck issues. We address the ***long-range dependencies*** with attention mechanism which will self-attend across the entire sequence, then cross-attend over all the self-attended modalities to capture the piece-by-piece and holistic views.
2. While the long-range dependencies are important due to the intrinsic nature discussed in the point #1, we must note that expressions are idiosyncratic (some people always look angry) and thus a concept named ***delta-attention*** [28] can be used where the change of the expressions matter more than static value of expression at the certain timestep. We use self-attention with a sliding window to evaluate if the hypothesis of long-range dependencies with a sliding window boosts the accuracy of emotion classification.
3. The self-attention mechanism on all the modalities separately, can get too big to handle very quickly. To manage the parameter count, and to keep the fused input sequence manageable for the cross-attention mechanism; we experimented with **deep cross-correlation analysis** (DCCA) [21, 14] to extract the useful features from the unimodal representation vectors.

For point #1, attention mechanism introduced in [23] addresses the shortcomings of a recurrent network and provides an intuitive method to capture the long-range correlations. This obviates the need of using Bi-LSTMs as done in many previous works [6, 15], which “cheats” by looking into the future and reverses the temporal order.

For point #2, I explored convolutional recurrent networks without any classification head and delta-self-attention to capture all the temporally local relations. And for point #3, we just experiment parameter reduction for the cross-fusion of the representation vectors of all three modalities.

We experimented with uni-modal accuracy and F1 scores, comparing those with accuracy on fused representations. We observe that the model proposed is successfully achieving scores very near to the current state-of-the-art models, with almost half the number of parameters as shown in the Table 2. We also gauge the effect of aligned versus unaligned modalities on our classification accuracy and find out that we do not need to explicitly align different modalities as attention naturally provides that alignment.

## 2 Novelty Statement

For all the approaches taken so far, the below mentioned missing gaps will be addressed in this project. In recurrent networks, looking at the entire sequence of data and outputting the last, single hidden state as its representation, often turns into the model forgetting information way past the current timestamp. They do not preserve the *long-range dependencies* [22] due to this bottleneck. This domino effect of updating a single hidden state each timestep can also result in exploding or vanishing gradients.

Second, data can be unaligned across modalities. A frowning face may relate to a pessimistic word spoken in the past. It’s not always between current word and current expression. And thus, third related point is, neutral expressions are quite idiosyncratic [8]. Some people may always look angry given their facial configuration. This raises the need for *delta attention* [28], we need to take cross-modal context plus the temporal context within each individual modality to negate the effect of “monotonous-across-the-time” features.

For these reasons, we propose the *delta* self-attention mechanism for all the modalities separately, attention provides an easy solution to the long-range dependencies and deals with the unaligned nature of the modalities with respect to the time because it’s a neural counterpart of alignment [23].

And lastly, the mechanism of fusing the modalities itself is not clearly figured out, the papers focusing on late fusion [17, 11] fall short in making any cross-correlation between the effect of each modality on the classification, generally early fusion methods [10] have been proven superior, this project focuses on building a hierarchical attention architecture where each modality has some representation vectors inferred by delta self-attended unimodal modules, which will be fused together with a deep cross correlation analysis (DCCA) [21, 14] module and finally processed with a cross-attention module to classify multiple modalities into 6 emotion classes: happy, sad, anger, surprise, disgust, and fear.

### 3 Related Work

Most of the work on this multimodal fusion phenomena was focused on the recurrent networks till around 2018, then the onset of transformers [5] piqued the community’s interest into attention mechanisms to solve these problems. MARN [27], a deep recurrent neural network to model the self-attentive view-specific and cross-view dual dynamics in human communication, uses information from hidden states of all LSTHMs (a custom cell to fuse hidden states of different modalities) at a timestep to regress coefficients to outline the multiple existing cross-view dynamics among them. We adopt this idea of using all hidden states with our delta-attended modules for visuals and acoustics, but do not use static word representation vectors as given in this paper. Instead we employ raw text and use a transformer for the verbal modality in order to catch the dynamic context.

With a slightly different goal of “Multi-modal Weakly Supervised Dense Event Captioning”, [19] explores an attention-based multimodal fusion model to integrate both audio and video information. The work done in “Attending to Emotional Narratives” proves that the attention-based mechanisms generalize well to multimodal time-series emotion recognition [25]. As previously stated, these mechanisms also align with our idea of using all hidden states of the recurrent network to encode visuals and acoustics, with the addition of a delta window. While their fusion strategies include multiplicative mixtures and multiplicative tangents or a direct off-the-shelf transformers, we are analyzing the correlations among the representation vectors before cross-attending and fusing them. We also have one more modality to deal with, which is the text/verbal modality, which adds more complexity to our model. Transformers are excellent at encoding information, but the Attention Narrative [25] paper finds that significant benefits in performance from adding recurrency.

More in-line with this work, “Hierarchical Transformer Network for Utterance-level Emotion Recognition” [12] explores the task of emotion recognition with a single modality of text and focuses on speaker-specific inferences through a lower-level transformer to model the word-level input and an upper-level transformer to capture the context of utterance-level embeddings. Our work also supports the notion of subjective intonations with the delta-attention which doesn’t take into account the idiosyncratic behavior and adds the facility to build the hierarchy across multiple modalities.

Here, we stress that a lot of work has gone into using the recurrent networks in order to learn the alignment across the modalities [26] because a word spoken at a timestep  $t$  might not directly relate to the facial expression at  $t$ , it might be related with other modalities representation at  $t \pm \epsilon$ . This is naturally taken care of by the attention-mechanism. “Multimodal Transformer for Unaligned Multimodal Language Sequences” [22] uses the cross-modal mechanism at the start to fuse the modalities in the following manner: Visual  $\rightarrow$  Acoustics || Language  $\rightarrow$  Acoustics, Visual  $\rightarrow$  Language || Acoustics  $\rightarrow$  Language and Acoustics  $\rightarrow$  Visual || Language  $\rightarrow$  Visual. These representations are later self-attended with a classification head on top. Our work is in the similar spirit but exact opposite in a sense that first we self-attend to capture the significant nuances within each modality with a sliding window and later we fuse those features with the cross-attention modules with skip connections from the representation space, making it an interesting question of which order works better and why.

Another aspect of multimodal fusion is that the idea of the *modality-based attention* is to prioritize one of the modalities at the word level. That is, when the lexical features are more relevant to capture emotions (i.e., informative words are used), the model should prioritize such features and vice versa. The work done on “Multimodal and Multi-view Models for Emotion

Recognition” [1] induces semantic information from a multimodal model into an acoustic-only network using a contrastive loss function. They talk about a hierarchical multimodal model that uses: 1) acoustic word representations derived from frame-level features, 2) a modality-based attention mechanism at the word level that prioritizes one modality over the other, and 3) a context-based attention mechanism that emphasizes the most relevant parts in the entire utterance.

This modality-based attention where one modality is prioritized over the other is presented by updating a GRU cell with weighted hidden state, giving lexical/verbal modality a higher weight. While the context-based attention module concentrates mass probability over the words that capture emotional states along the sequence. Our work assumes that all 3 modalities are of equal weight, but we will prune the insignificant contributions by any modality with the correlation analysis and cross-attention. Similar work mentions “Found in Translation: Learning Robust Joint Representations by Cyclic Translations Between Modalities” [18] where during testing, we only need the source modality for prediction which ensures robustness to noisy or missing target modalities. This is accomplished by first getting the directional representation vectors from the source modality to a target modality, then back from target modality to the source modality. If there’s a third modality, then the cyclic representation gained from the first two modalities will be used as a source while the third modality will be the target one. This might generate a dependence on the order of the modalities and is not parallel for all the modalities. The model proposed here would be parallel for all the modalities and only need all the representation at the end stage of cross-attention.

From the above mentioned all eight works, our work closely matches with the multimodal transformer described in [22]. Let’s briefly describe it here: at the high level, they have used directional pairs of cross-modal attention and merged their representations through a feed forward self-attention head to classify the emotion class. Reader should note that this directional cross-modal concepts adds 6 different modules in order to achieve the fusion, while our work uses only 3 modules by putting self-attention before cross-attention.

Suppose there are two modalities  $\alpha$  and  $\beta$  and their time-series sequences are represented as  $X_\alpha \in \mathbb{R}^{T_\alpha \times d_\alpha}$  and  $X_\beta \in \mathbb{R}^{T_\beta \times d_\beta}$  where  $T(\cdot)$  is the sequence length and  $d$  is the dimension of the features. Inspired by the attention architecture in [23], the Queries are  $Q_\alpha = X_\alpha W_{Q_\alpha}$ , Keys are  $K_\beta = X_\beta W_{K_\beta}$  and Values are  $V_\beta = X_\beta W_{V_\beta}$  where  $W_{Q_\alpha} \in \mathbb{R}^{d_\alpha \times d_k}$ ,  $W_{K_\beta} \in \mathbb{R}^{d_\beta \times d_k}$  and  $W_{V_\beta} \in \mathbb{R}^{d_\beta \times d_k}$  are the weights. The cross-modal attention with  $\beta$  as the source or the base modality and  $\alpha$  as the target modality is represented by

$$Y_{\beta \rightarrow \alpha} = \text{CrossModalAttn}_{\beta \rightarrow \alpha}(X_\alpha, X_\beta) \in \mathbb{R}^{T_\alpha \times d_v} \quad (1)$$

$$= \text{softmax} \left( \frac{Q_\alpha K_\beta^T}{\sqrt{d_k}} \right) V_\beta \quad (2)$$

$$= \text{softmax} \left( \frac{X_\alpha W_{Q_\alpha} W_{K_\beta}^T X_\beta^T}{\sqrt{d_k}} \right) X_\beta W_{V_\beta} \quad (3)$$

This blocked is stacked multiple times (say,  $D$  times) to build a multi-blocked cross-attention transformer modules for all 6 directional modality pairs. To make sure that each sequence has temporal awareness, they pass the output of a convolutional layer to these transformers:

$$\hat{X}_{L,V,A} = \text{Conv1D}(X_{L,V,A}) \quad (4)$$

Transformers by themselves are order-invariant, thus we must add the positional embeddings as,

$$Z_{L,V,A}^{[0]} = \hat{X}_{L,V,A} + \text{PE}(T_{L,V,A}, d) \quad (5)$$

Thus, the cross-modal transformer computes feed-forwardly

$$Z_{\beta \rightarrow \alpha}^{[0]} = Z_\alpha^{[0]} \quad (6)$$

$$\hat{Z}_{\beta \rightarrow \alpha}^{[i]} = \text{CrossModalAttn}_{\beta \rightarrow \alpha}^{[i]}(\text{Norm}(Z_{\beta \rightarrow \alpha}^{[i-1]}), \text{Norm}(Z_\beta^{[0]})) + \text{Norm}(Z_{\beta \rightarrow \alpha}^{[i-1]}) \quad (7)$$

$$Z_{\beta \rightarrow \alpha}^{[i]} = \text{FeedForward}_{W_{Q_\alpha}, W_{K_\beta}, W_{V_\beta}}^{[i]}(\text{Norm}(\hat{Z}_{\beta \rightarrow \alpha}^{[i]})) + \text{Norm}(\hat{Z}_{\beta \rightarrow \alpha}^{[i]}) \quad (8)$$

Finally, the concatenation  $[Z_{\beta \rightarrow \alpha}^{[D]}; Z_{\gamma \rightarrow \alpha}^{[D]}]$  is passed through a sequence model to make temporally dependent predictions.

Now let's talk about the model proposed in this work and the improvements it has made in the results.

## 4 Methodology

Here we describe the proposed hierarchical delta-attention model for multimodal fusion with three modalities, we denote verbal or language modality as L, visual modality as V, and vocal or acoustics modality as A. On a high level, first, each modality will be separately self-attended to extract the features or representation vectors. We will discuss the delta window size and its implementation for this attention module in section 4.1. After getting the representation vectors, we pass them through a DCCA component as discussed in section 4.2 to only extract the features which contribute in learning the context through all the modalities together. Finally, we use skip connections of the individual representation vector and the correlated vector to cross-attend across all the modalities in section 4.3 and classify the emotion category with the classification head of top of cross-attention module. The overall architecture is discussed in the section 4.4.

### 4.1 Delta Self-Attention

We denote the input sequences for three modalities L, V, A as  $X_{\{L,V,A\}}$  respectively where  $X_{\{L,V,A\}} \in \mathbb{R}^{T_{\{L,V,A\}} \times d_{\{L,V,A\}}}$ . Here  $T_{(\cdot)}$  is the time-series sequence length and  $d_{(\cdot)}$  is the feature dimensions. For ease of exposition, we now talk about any one modality  $M \in \{L, V, A\}$  and can assume that the same treatment will be applied to all the modalities. Now we initialize Queries as  $Q_M = X_M W_{Q_M}$ , Keys as  $K_M = X_M W_{K_M}$  and Values as  $V_M = X_M W_{V_M}$  where  $W_{Q_M} \in \mathbb{R}^{d_M \times d_k}$ ,  $W_{K_M} \in \mathbb{R}^{d_M \times d_k}$  and  $W_{V_M} \in \mathbb{R}^{d_M \times d_v}$  are the trainable weight parameters with  $d_k$  and  $d_v$  as feature dimensions of query/key and value representations respectively. Here we are assuming that the bias is absorbed into the weight matrix itself, and the  $X_M$  accounts for it by adding an extra feature dimension.

To add the temporal component to this basic attention module, we design a convolution layer with kernel  $\text{kernel}_M$  of size  $d_{ch}$  and get

$$\hat{X}_M = \text{Conv1D}(X_M, \text{kernel}_M) \in \mathbb{R}^{T_M \times d_{ch}} \quad (9)$$

Now, instead of using the default sinusoidal position embeddings, we use temporally relative positional embeddings. And instead of adding these embeddings to  $\hat{X}_M$ , but to the logit calculation itself, we can see how much  $d_{ch}$  features at timestep  $t_i \in T_M$  attend to the features at timestep  $t_j \in T_M$  where  $i \leq j$ .

More specifically, we will add the relative positional embeddings to the Key vector as

$$Z_M = \text{DeltaSelfAttend}_M(\hat{X}_M) \in \mathbb{R}^{T_M \times d_{ch}} \quad (10)$$

$$= \text{softmax} \left( \frac{Q_M K_M^T + \text{RPE}_M}{\sqrt{d_k}} \right) V_M \quad (11)$$

where for the timestep  $t_i$  and  $t_j$ , the value of  $\text{RPE}_{Mij}$  depends only on  $\hat{X}_{Mi} \in \mathbb{R}^{d_{ch}}$  and  $\hat{X}_{Mj} \in \mathbb{R}^{d_{ch}}$  and thus Relative Position Embeddings  $\text{RPE}_{Mij} = (\hat{X}_{Mj} - \hat{X}_{Mi}) \cdot W_{\text{RelPos}_M} \in \mathbb{R}^{T_M \times T_M}$  and  $W_{\text{RelPos}_M} \in \mathbb{R}^{d_{ch} \times T_M}$  are the additional learnable parameters we are using which **emphasizes the change or relative nuances in the time-series sequence more than the absolute values**.

These parameters can be shared across the heads of a multi-headed attention module and more each additional layer, we add additional  $d_{ch} \times T_M$  parameters.

To stack multiple attention heads, the outputs of all the heads are concatenated and the final representations are projected as

$$\text{MultiHeadedDeltaSelfAttn}(X_M) = [Z_{M0}; Z_{M1}; \dots; Z_{MH}] W_{O_M} \in \mathbb{R}^{T_M \times d_o} \quad (12)$$

where  $H$  is the number of heads and  $W_{OM} \in \mathbb{R}^{Hd_{ch} \times d_o}$ ,  $d_o$  being the output dimension. We call it  $MHDSA(X_M)$  for brevity. The architecture of the delta self-attention module is depicted in Figure 1.

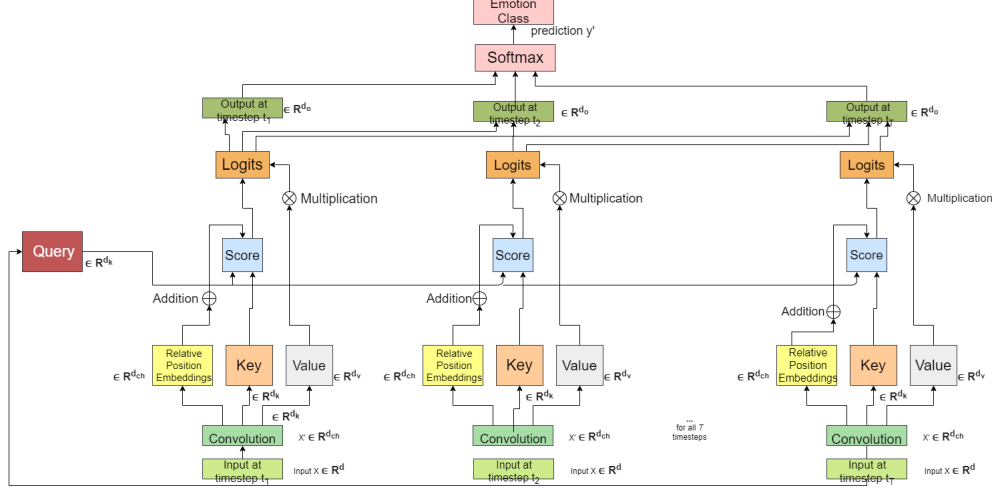


Figure 1: Delta Self-Attention Module: The core component of our hierarchical attention architecture which takes into account the idiosyncratic behaviour in *long-range dependencies*.

## 4.2 Deep Canonical Correlation Analysis

At this point, we will have outputs from  $MHDSA(X_L)$ ,  $MHDSA(X_V)$  and  $MHDSA(X_A)$ . Compared to a position-agnostic self-attention module, our module will have  $T_M^2 \times H + d_{ch}$  extra parameters and additional complexity incurred by  $O(T_M^2 + d_{ch})$  multiplications, and  $O(d_{ch} + T_M^2)$  element-wise additions. This makes the minibatch gradient descent restrictive in the number of batch size. And this numbers repeat for each modality, making the fusion extremely expensive. Here we discuss a the Deep Canonical Correlation Analysis (DCCA) discussed in previous work [21] related to the cross-modal feature extractors. “Canonical Correlation Analysis (CCA) is a statistical technique for finding a linear projection for two views into a common space where they are maximally correlated. DCCA is a non-linear version of CCA.”

As the paper [21] talks about, we reconstruct the modality representation from this DCCA, reconstructions will have two main advantages:

1. The reconstructions will have smaller dimensions, making it computationally more feasible to learn the parameters with minibatch gradient descent.
2. Now the per-modality representations are not only self-attended but also correlated with the self-attention from the rest of the modalities.

Thus we only extract the representations which is useful in extracting out the context.

DCCA maximizes the correlation among the input modalities, and enhances it with the reconstructions from the encoded view.

For simplicity of computations, we have used a 2 layer convolution network as an encoder  $E(Y_M, \theta_{E_M})$ . The objective function is as follows

$$\min_{\forall M \in \{L, V, A\} \theta_{E_M}, \theta_{D_M}} -CCA(E(Y_{M \in \{L, V, A\}}, \theta_{E_{M \in \{L, V, A\}}})) \quad (13)$$

where  $Y_M = MHDSA(X_M) \in \mathbb{R}^{T_M \times d_o}$  and  $\hat{Y} = CCA(E(Y_M, \theta_{E_M})) \in \mathbb{R}^{T_M \times d_r}$  and  $d_r \ll d_o$ .  $Y_M$  are the self-attended features as the inputs to DCCA encoders and  $\hat{Y}$  are the outputs. It is shown in Figure 2a.

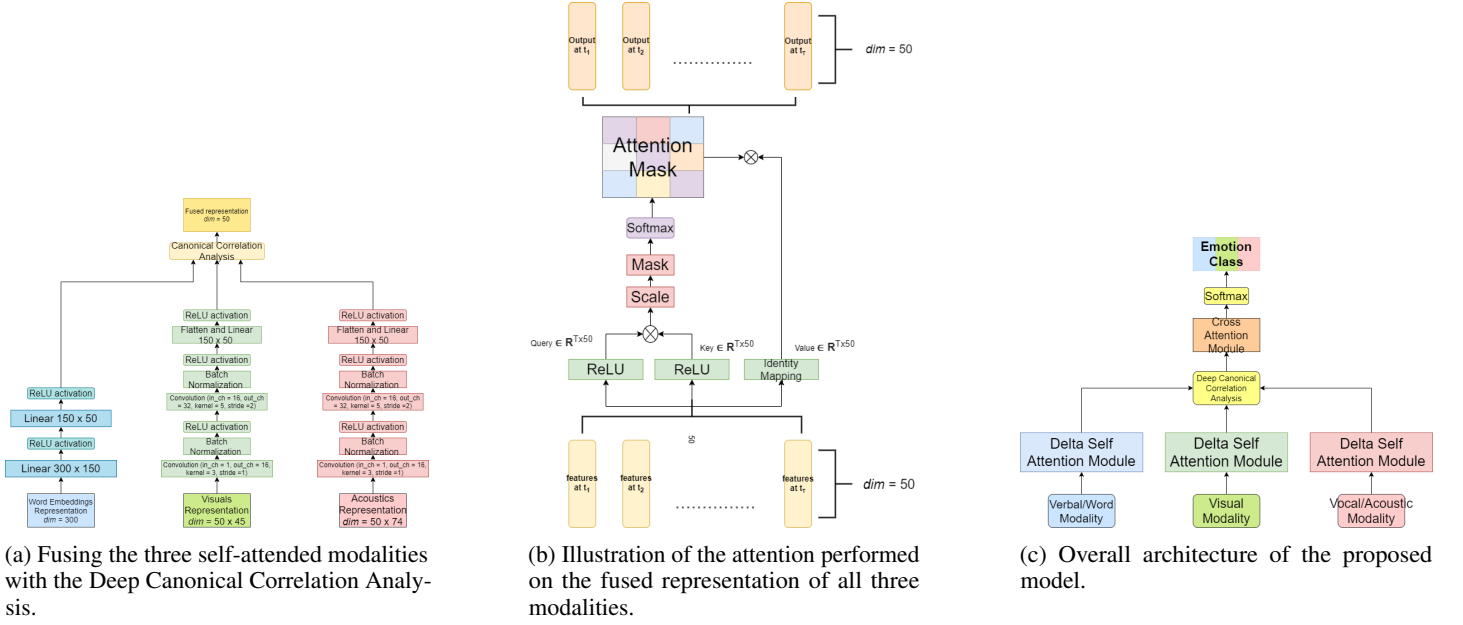


Figure 2: Architectures of the two core components (left, and center) of the model depicted (right).

### 4.3 Cross-Modal Attention

Now we have this representation vector  $\hat{Y}$  which is the correlation vector among all the 3 modalities  $\{L, V, A\}$ . For ease of keeping track of which vector represents which modalities, we call  $\hat{Y}$  by  $\hat{Y}_{Fused} \in \mathbb{R}^{T_{Fused} \times d_r}$  which shows that this vector is a learned mixture of all 3 modalities. Here, the motivation behind stacking an attention module on top of a cross-correlation analysis module is that

1. We hypothesise that while correlation analysis fuse and extract the representations which are most influential for the classification, attention would temporally scan through this fused sequence and still be able to make temporal correlations which might not have been captured by the first pass of uni-modal attention.
2. While this is not technically “cross”-attention because of it being the computations on only one representation; we can consider it as a self-attention on cross-correlated features. It would be still interesting to show how the stacking of an attention module effects the results.

The procedure is just like a basic attention module, shown in Figure 2b, we will briefly describe it as

$$Z_{Fused} = \text{MultiModalAttn}(\hat{Y}_{Fused}) \in \mathbb{R}^{T_{Fused} \times d_t} \quad (14)$$

$$= \text{softmax} \left( \frac{Q_{Fused} K_{Fused}^T}{\sqrt{d_t}} \right) V_{Fused} \quad (15)$$

$$= \text{softmax} \left( \frac{\hat{Y}_{Fused} W_{Q_{Fused}} W_{K_{Fused}}^T \hat{Y}_{Fused}^T}{\sqrt{d_t}} \right) \hat{Y}_{Fused} W_{V_{Fused}} \quad (16)$$

The Queries are  $Q_{Fused} = \hat{Y}_{Fused} W_{Q_{Fused}}$ , Keys are  $K_{Fused} = X_{Fused} W_{K_{Fused}}$  and Values are  $V_{Fused} = X_{Fused} W_{V_{Fused}}$  where  $W_{Q_{Fused}} \in \mathbb{R}^{d_{Fused} \times d_t}$ ,  $W_{K_{Fused}} \in \mathbb{R}^{d_{Fused} \times d_t}$  and  $W_{V_{Fused}} \in \mathbb{R}^{d_{Fused} \times d_t}$  are the weights. On this level, it is expected that the ample number of parameters and fusion would not require us to stack big number of attention heads.

### 4.4 Overall Architecture

Once we get  $Z_{Fused}$  after processing through sections 4.1, 4.2 and 4.3; we can use a softmax layer for the 6 class classification,

$$\text{ClassLabel} = \text{softmax}(\text{Linear}(Z_{Fused})) \quad (17)$$

	Epochs	Learning Rate	Mini Batch Size	Weight Decay
SelfAttn <sub>L</sub>	10	1e-6	32	1e-4
SelfAttn <sub>V</sub>	10	1e-5	8	1e-4
SelfAttn <sub>A</sub>	10	1e-5	8	1e-4
DCCA	100	2e-4	4	1e-6
CrossAttn <sub>Fused</sub>	5	1e-5	8	1e-6

Table 1: Table showing the optimal hyperparameter selected for the given 5 main modules of the model with the Adam optimizer. Due to the lack of computational resources, each module has been trained separately, their states and outputs saved and later loaded into the memory for the modules higher up in the hierarchy.

Now we briefly discuss the hyper-parameter selection. Most of the attention literature uses Adam optimizer and we found that for this model, it gave stable decrease in the loss as well. Due to the large parameter count, model time complexity and limited computational resources; we only tried handful of hyper-parameter setups. We split train:validation:test data into approximately 18.5k:2.25k:2.25k sample ratio, which is a 80:10:10 percentage ratio. We used the validation set for hyper-parameter tuning, upon finding the satisfactory setup, we merged validation and train set into one and re-learned the model with it; testing the generalize-ability of the model only on the test set. The selected hyper-parameters are given in Table 1. The model is shown in Figure 2c.

Inference follows the same method of generating three separate uni-modal representations in parallel, which then can be fused together with a DCCA + Cross-Modal Attention + softmax head.

## 5 Dataset

Multimodal Opinion Sentiment and Emotion Intensity (CMU-MOSEI)<sup>1</sup> [2] is the largest and the latest dataset of sentence level sentiment analysis and emotion recognition. It contains more than 65 hours of annotated video from more than 1000 speakers and 250 topics. It has around 23k samples, each with around 1000 text features, 300 visual frames at 15Hz sampling rate, and 150 acoustic features at 20Hz sampling frequency. Most of the transformer based papers have been benchmarked on this dataset, because of its size and the variety in “in-the-wild” emotions. Thus, this project will also use this dataset, to be able to compare the results fairly.

CMU-MOSEI has sentiment and 6 emotion scores. Sentiment is in range [-3,3] and emotions in range [0,3]. Labels are in the order of: (sentiment, happy, sad, anger, surprise, disgust, fear). We only deal with these 6 emotions and not with the sentiment (positive, neutral, negative) classes. As done in the previous works [22, 2, 24, 27, 18], we will evaluate the model’s efficiency using the following metrics: accuracy of classification given the 6 classes ( $Acc_6$ ), F1 score, mean absolute error MAE, and comparison with the human prediction score.

### 5.1 Verbal

The dataset comes with high-level features in form of glove embeddings having 300 dimensions. But for the purpose of using a transformer, we used raw text to get the advantage of dynamic context alignment. The CMU-MOSEI SDK provides the facility to align the visual and vocal computational sequences with the verbal as the base modality reference.

### 5.2 Visual

Here we use high-level extracted features (dimension=85) in form of MultiComp OpenFace [3]; this consists of a set of 68 facial landmarks, 20 facial shape parameters, facial HoG features, head pose, head orientation and eye gaze [13].

<sup>1</sup><https://github.com/A2Zadeh/CMU-MultimodalSDK>



### 5.3 Vocal

COVAREP software is used to extract the high-level acoustic features (dimension=74): 12 Mel-frequency cepstral coefficients, pitch, voiced/unvoiced segmenting features, glottal source parameters, peak slope parameters and maxima dispersion quotients. All extracted features are related to emotions and tone of speech [13].

## 6 Experiments

Due to the novelty of the concept and components, we mainly focused the efforts on building the model architecture and trying out various layers more than trying the same architecture on various datasets. Thus, these experiments are only on the dataset described in section 5, CMU-MOSEI [2].

### 6.1 Pre-processing the Data

For text modality, we processed raw text sequences to remove the “sp” tokens indicating speech pauses as it is helpful to focus more on the context and semantics of the words for this task. And it generally also improved the alignment task, as there are more visual and acoustics features per word.

Next we limited the sentences to 510 tokens at most, prefix-ed it with a classification token “[CLS]” and suffixed it with the separation token “[SEP]”. The intuition behind this is that we want to train each uni-modal self-attention module separately, so we can compare the uni-modal accuracy with the multi-modal fusion accuracy, and also have some objective to learn the representation vectors.

To have the same dimensionality for the fusion at later stage, we take word-level granularity and for the words spoken at each interval (note that there is interval information along with features for all 3 modalities in the dataset), we pad and stack the visual (Facet 4.2) and acoustic (COVAREP) sequences, making all three sequences for a certain time interval  $[t, t + \epsilon]$  having the same length. To make sure that the attention modules don’t interpret padded values (“[PAD]” for words and 0s for the other two), we use attention masks which will mask away the padded values.

### 6.2 Model Selection

We trained the uni-modal self-attention modules for all 3 modalities L, V, A separately first, this can be done in parallel as these 3 modules are independent of each other after the initial interval alignment performed in the pre-processing step. The selected hypermeter is given in Table 1. The hypermeter selection method of splitting the dataset into train:valid:test sets is given in the section 4.4.

### 6.3 Performance and Baseline

Here we describe the experiments and the rationale behind it, and in section 7, we will describe the findings of those experiments.

We will compare our results to the baseline technique of cross-attention and then self-attention in [22], which we are closely comparing our method to and the state-of-the-art results presented in the work done on “A Transformer-based joint-encoding for Emotion Recognition and Sentiment Analysis ” [4]. The fusion technique in this work is mainly focused on the emotion classification through capturing the cross-modal context, thus the classification accuracy on all 6 emotion classes as well as the F1 score (due to imbalance between sample per class) are the primary measures.

We first use our classification head on all 3 unimodal delta self-attention module individually, to compare the gains of the proposed multimodal fusion technique later. Here we expect that multimodal fusion will add more context to the data and thus, the gains should be comparably higher. Third experiment is between **aligned** and **unaligned** data, with **aligned** data, we have aligned the sequence intervals of all 3 modalities according to the base text modality, parts of any modality not in the interval have been discard; with the **unaligned** data, we are not discarding any parts regardless of their inclusion in any interval, nor we have any “base” or reference modality. Our expectation is that aligned data of course gives us an indicator of which range to look into for a spoken word’s effect

Description	CMU-MOSEI Emotion Classification													
Task	Overall		Class: Happy		Class: Sad		Class: Anger		Class: Surprise		Class: Disgust		Class: Fear	
Metric	Acc <sub>6</sub>	F1	Acc <sub>2</sub>	F1	Acc <sub>2</sub>	F1	Acc <sub>2</sub>	F1	Acc <sub>2</sub>	F1	Acc <sub>2</sub>	F1	Acc <sub>2</sub>	F1
Unimodal Delta Self-Attention														
Text Only	44.6	76.2	64.7	71.9	72.1	68.3	79.1	74.5	82.3	71.5	83.9	72.6	80.1	70.0
Visuals Only	50.2	78.2	68.4	<b>73.9</b>	71.3	67.0	80.3	<b>76.8</b>	80.4	69.3	81.4	71.0	85.4	79.4
Acoustics Only	49.3	77.1	64.5	70.3	72.0	68.5	75.2	72.4	79.1	67.2	84.9	74.8	81.5	72.3
Self-Attended and Canonically Correlated Representation														
Aligned Data	48.6	76.5	68.7	71.7	69.8	69.1	81.4	73.7	84.4	77.0	84.3	74.0	88.4	90.3
Unaligned Data	47.3	74.8	66.3	68.4	72.6	70.3	80.0	73.1	83.4	75.4	83.2	73.1	84.0	90.1
Multimodal Fused Hierarchical Attention														
Aligned Data	49.7	78.2	<b>72.1</b>	72.6	<b>75.4</b>	<b>73.7</b>	83.2	75.9	<b>89.2</b>	87.0	<b>87.1</b>	<b>84.8</b>	86.3	<b>93.2</b>
Unaligned Data	49.9	77.5	71.8	70.4	73.2	71.1	<b>83.9</b>	74.3	87.6	<b>90.3</b>	87.0	80.3	<b>89.3</b>	90.8
Comparison with SOTA and MulT														
MulT[22]	<b>50.7</b>	<b>81.6</b>	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Graph-MFN[29]	45.0	77.0	66.3	66.3	60.4	66.9	62.6	72.8	53.7	85.5	69.1	76.6	62.0	89.9
SOTA1[4]	44.4	N/A	65.0	64.0	72.0	67.9	81.6	74.7	90.5	86.1	85.9	83.6	89.1	84.0
Previous SOTA2[29]	44.6	76.0	57.8	66.6	58.9	60.8	56.0	71.4	52.2	85.4	65.2	71.4	56.7	89.9
Previous SOTA3[29]	44.7	76.4	66.5	71.0	59.2	61.8	60.5	72.0	53.3	85.4	67.0	73.2	60.0	89.9

Table 2: Table showing results of experiments on the test date for unimodal performance of the delta self-attended modules, fused DCCA modules, and then multi-modal hierarchical attention modules for both aligned and unaligned data. The results are compared with MulT, G-MFN, SotA1, SotA2, and SotA3.

on person’s intonation or facial expression, and thus also on the classification; but it’s not always necessary that the facial expression or the intonation depends entire on the word’s spoken in that interval only.

If we find out that we do not need to align the data, it will be a great time-saver for real-time inference. Our hypotheses is that due to the natural alignment provided by cross-attention, we wouldn’t need our data to be aligned for this architecture.

## 7 Results

Here we evaluate the results in the table 2 quantitatively. We couldn’t compare out per class binary classification results with the MulT[22] model as they hadn’t reported it, so it’s unfair to claim that this model can outperform MulT on per class basis. We can still observe a couple of things from the all class classification accuracy Acc<sub>6</sub> and the F1 score: 1) Our model is giving very competitive results to the MulT model. We had only used 3 base attention modules in place of 6 in the MulT model. This would significantly reduce the computation requirement. 2) We can see that this multi-modal fusion has been effective in capturing the context of the situation because of its superior performance over uni-modal models. 3) Given that the model is performing on-par for unaligned data, we can prove our hypothesis that attention would indeed naturally provide the alignment and thus we do not explicitly need to align the sequences as a pre-processing step.

## 8 Discussion and Conclusions

In this work, we experimented with the uni-modal accuracies of all 3 modalities, comparing those with the accuracy on fused representations. Our fusion techniques show that if we self-attend all the modalities separately for a fixed delta window and then fuse those attended representations with a deep correlation analysis, and then cross-attending that fused representation, we get near-to-the-SOTA accuracy. Comparing this model to a very similar-in-nature model [22], we prove that we can achieve almost similar results with half the parameters and thus half the computation power needed for the previous work as shown in the Table 2. We also gauge the effect of aligned versus unaligned

modalities on our classification accuracy and find out that we do not need to explicitly align different modalities as attention naturally provides that alignment.

Our observation is that aligning the entire data doesn't improve the accuracy by a significant margin, while we also agree that adding more depth to the DCCA in section 4.2 would certainly give us better results as the parameter count would go up. Generally, with multimodal fusion, we need a lot of parameters to capture all the nuances and complexity attached with cross-modal context and capturing these long-range minute dependencies might be improved as the parameter count go up. Thus, currently, the best way to improve accuracy seems to be adding more parameters on the upper sections of the model. We also suggest the following other ideas for the future work:

1. use of finer granularity of modalities (subword, character etc),
2. use of different attention mechanisms to cover long-range dependencies over and across the modalities like building a part of speech trees to capture the relation between nouns and adjectives as in aspect based sentiment analysis,
3. use of generative adversarial networks to generate and discriminate between fake and real features (can detect sarcasm if the model can efficiently remove the fake positive verbal connotation),
4. variable window delta-attention,
5. handling larger dimension-ed data efficiently across the modalities,
6. inferring missing features of a modality with the help of present modalities,
7. inclusion of one more modality like "non speech voices" like cry, whimper; and,
8. addressing the distinction between the timescales of concepts of emotion and mood.

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